2. The method of claim **1**, wherein the first medical imaging modality is one of a magnetic resonance imaging (MRI) device, a computed tomography (CT) device, a positron emission tomography (PET) device, an ultrasound device, a dynaCT device, an angiogram device, and a mammography device, and the second medical imaging modality is another of the MRI device, the CT device, the PET device, the ultrasound device, the dynaCT device, the angiogram device, and the mammography device.

3. The method of claim **1**, wherein the first image and the second image are three-dimensional (**3**D) images, respectively.

4. The method of claim **1**, wherein generating comprises generating with the machine-learned generator having been trained with learned shape features in the domain-invariant space decomposed from multi-modal image pairs representing a region of interest, images of each of the multi-modal image pairs having been generated by the first medical imaging modality and the second medical imaging modality, respectively.

5. The method of claim **4**, wherein generating comprises generating with the machine-learned generator having been trained with the shape images decomposed by machine-learned encoders of an image translation network.

6. The method of claim **4**, wherein images of the multi-modal image pairs are not aligned.

7. The method of claim **1**, wherein generating comprises generating by the machine-learned generator having been trained with latent similarity loss, and the discriminators having been trained with adversarial loss.

8. The method of claim **1**, wherein registering comprises registering the first image with the second image using a first of the deformation fields when the first image is a moving image and the second image is a fixed image, and registering the second image with the first image using a second of the deformation fields when the second image is the moving image and the first image is the fixed image.

9. The method of claim **1**, wherein the discriminators are desriminators of a generative adversarial network (GAN).

10. The method of claim **1**, wherein generating comprises generating with the machine-learned discriminators having been trained based on translated images from a machine-learned image translation network.

11. A system for unsupervised multi-modal image registration, the system comprising:

a memory configured to store a first image and a second image, the first image being generated by a first modality and the second image being generated by a second modality; and

an image processor in communication with the memory, the image processor configured to:

generate a prediction of deformation fields between the first image and the second image in response to input of the first image and the second image to a machine-learned generator having been trained in domain-invariant space and machine-learned discriminators having been trained in image space; and

register the first image and the second image using one of the predicted deformation fields.

12. The system of claim **11**, further comprising a display in communication with the image processor, the display being configured to display the registered first image and second image, at least one of the deformation fields, or the registered first image and second image and the at least one deformation field.

13. The system of claim **11**, further comprising:

the first modality in communication with the image processor; and

the second modality in communication with the image processor.

14. The system of claim **13**, wherein the first modality is one of a magnetic resonance imaging (MRI) device, a computed tomography (CT) device, a positron emission tomography (PET) device, an ultrasound device, a dynaCT device, an angiogram device, and a mammography device, and the second modality is another of the MRI device, the CT device, the PET device, the ultrasound device, the dynaCT device, the angiogram device, and the mammography device.

15. The system of claim **11**, wherein the first image and the second image are two-dimensional (2D) images, respectively.

16. A method for machine training unsupervised multi-modal image registration in a medical imaging system, the method comprising:

defining a multi-task network with an objective function including a loss term representing latent space similarity and a loss term representing image space similarity; and

machine training the multi-task network to estimate a prediction of a deformation field for registration between a first image generated by a first modality and a second image generated by a second modality, the machine training being based on latent shape features in the latent space decomposed from multi-modal image pairs representing a region of interest, images of each of the multi-modal image pairs having been generated by the first modality and the second modality, respectively.

17. The method of claim **16**, wherein images of the multi-modal image pairs are not aligned.

18. The method of claim **16**, further comprising storing, by a memory, the machine-trained multi-task network.

19. The method of claim **16**, wherein the machine training is also based on translated images generated from the multi-modal image pairs being input into an image translation network.

20. The method of claim **16**, further comprising registering the first image and the second image using the machine trained multi-task network.

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